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The Relationship between Training Load Measures and Next-Day Well-Being in Rugby Union Players

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Abstract: The aim of this study is to identify the relationship between different internal and external load measures and next day subjective wellbeing. With institutional ethics approval, ten academy rugby union players (Five forwards, and five backs) with a local National League One club agreed to participate in the study (aged; 18.4 ± 1.0 years, height; 181.3 ± 5.9 cm, body mass 85.9 ± 13.0 kg, VO_{2max} 56.2 ± 6.8 mL·kg^{-1}·min^{-1}). Before the 6-week in-season data collection period, participants completed an incremental treadmill test to determine lactate thresholds at 2 mmol·L^{-1} (LT) and 4 mmol·L^{-1} and the heart rate blood lactate (HR-BLa) profile for individualized training impulse (iTRIMP) calculations. Internal training load was quantified using Banister's TRIMP, Edward's TRIMP, Lucia's TRIMP, individualised TRIMP and session-RPE. External training load was reported using total distance, PlayerLoad^{TM}, high-speed distances (HSD) > 18 km·h^{-1} and >15 km·h^{-1}, and individualized high-speed distance (iHSD) based on each player's velocity at OBLA. On arrival and prior to all training sessions players completed a well-being questionnaire (WB). Bayesian linear mixed model analysis identified that a range of internal and external load measures explained between 30% and 37% of next-day total wellbeing and between 65% and 67% of next-day perceived stress. All other internal and external load measures demonstrated very weak to moderate relationships (R^2 = 0.08 to 0.39) with all other wellbeing components. Internal sRPE, iTRIMP and bTRIMP loads alongside external HSD loads provide coaches with the most practical measures to influence players' perceived wellbeing.

Keywords: wellbeing; training impulse; fatigue; internal load; external load; team sports

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1. Introduction

The general aim of athletic training is to induce a physiological stress which stimulates adaptation [1]. Athlete monitoring of the training process plays an important role in the decisions that are taken surrounding manipulations to training. One of the purposes of athlete monitoring is to better understand the relationship between what is done and how players may respond [2]. This has commonly been termed the dose-response (D-R) relationship [3]. Banister et al. [4] suggested that training can produce two responses (fitness and fatigue) and in its simplest form, an athlete's current fitness minus accrued fatigue will determine a players' performance potential at any given time. Thus, to better understand the performance potential of a player, coaches need to be able to quantify aspects of each training session with measures that are related to changes in measures of player's fitness and fatigue [2]. The aim being for coaches to determine an appropriate dose-response relationship enabling them to take a proactive rather than reactive role. Elite rugby union has seen an increase in match-play activity profiles in combination with shorter recovery times [3]. Forwards are involved in more contacts/collisions, alongside an increase in repeated high-speed efforts and less with the ball being out of play for all player positions [5,6]. Thus, increasing the need for coaches to provide players with sufficient recovery. Questionnaires have been used in team sports to manage well-being although much of this is done in a reactive manner [7,8]. However better understanding of how training load (TL) affects well-being could provide coaches and practitioners with the tools to monitor and manipulate training to manage players' well-being better and thereby reducing the potential risk of injury or excessive fatigue [7].

Whilst previous dose-response studies have identified a range of internal load measures which can be applied to monitor and assess fitness in rugby union [9,10], there is limited research on the relationship between TL metrics and the resulting exercise-induced fatigue, perceived or otherwise. Currently coaches typically use well-being questionnaires to quantify subjective fatigue and recovery. In addition, various sprint performance, jump performance and biochemical/hormonal/immunological measures are used to assess objective fatigue [11]. Current research is descriptive in nature, focusing on identifying trends in fatigue markers during and post periods of high-intensity training during preseason [12,13] or short micro-cycles which included match-play [7,14,15]. Current evidence has identified that multi-item self-report measures such as Recovery-Stress questionnaire (REST-Q) and Profile of Mood State (POMS) questionnaire demonstrate the strongest validity and reliability as measures of well-being [4]. Despite the validity and reliability of REST-Q and POMS questionnaires, the most commonly used measures of well-being in an applied setting are more brief, custom self-report measures [1,5–7]. These custom self-report measures typically report player's perceptions of muscle soreness, fatigue, sleep quality, stress and mood. The relationships between these custom self-report measures have identified that summed wellness (weekly score relationships with phases of training; pre-season and in-season) and training load measures typically demonstrate negative relationships [8–10]. Alternatively, mixed linear models have demonstrated weak relationships between post-match or match loads and next-day well-being scores [11,12]. An additional weakness of the current research is the statistical analysis applied. The strength of relationships between self-report measures and training loads are stronger in studies that have applied correlation measures [1]. In contrast, those studies that have used mixed models to account for within repeated measures of each athlete have identified smaller relationships [1,7]. Collectively, previous research suggests that following match-play and during periods of high-intensity training, both countermovement jump (CMJ) metrics and well-being questionnaires are sensitive to changes in players' fatigue. Importantly, descriptive trends do not identify the presence of a relationship between load and fatigue measures. Therefore, to better understand the suitability of commonly used TL metrics to influence well-being, the dose-response relationship needs to be assessed. During the competitive in-season, fatigue is typically managed to optimise players' match performance.

Leading into a match, coaches typically look to taper training to allow players to recover and maximise match performance [16]. This 'tapering' process is achieved by altering several components such as training volume, intensity, and frequency [13] alongside the duration of the taper. Meta-analysis of tapering strategies has identified that reducing training volume was most sensitive to improving performance [13,14]. Reductions of 41% to 60% in training volume over 8 to 14 days have demonstrated an average improvement of 1.96% in performance measures in individual sports (runners, cyclists, rowers, swimmers and triathletes) [13]. The challenge in team sports is the need to manage tapering for matches on a weekly basis, where an 8 to 14-day taper isn't practical. Consequently, within team sports there is a need to better understand players' response to daily training loads so that coaches can evaluate and adapt the subsequent days training to ensure players are sufficiently recovered to optimise their match performance that week. By identifying the relationship between a range of commonly used internal and external load measures and next day subjective well-being would help inform coaches on the changes in TL required to elicit a desired response in players' well-being. This 'tapering' process is achieved by reducing the TL in the final days before a match to allow players to recover from the higher TL experienced earlier in the training week. The challenge for coaches is to improve our understanding how much recovery a player needs to optimise their match-day performance. Therefore, understanding the relationship between measures of TL and next-day well-being during the competitive in-season can help improve coach's ability to better understand players recovery.

Therefore, the aim of the study was to examine the changes in players' well-being following the previous days' training during an in-season period. If next-day wellbeing demonstrates a strong relationship with the previous days training coaches could use the information to decide if a player requires more recovery and thus adapt the subsequent training that day. On the other hand, if such relationships are absent it questions the use of both dose and response measures used to suitably inform such a process.

2. Materials and Methods

2.1. Experimental Approach to the Problem

The aim of this study is to evaluate the relationship with daily TL and next-day-(morning) well-being during the competitive in-season. Participants were recruited from the first 15 squad two weeks prior to the study. The study was conducted over a seven-week period in the English winter (October to December), eight weeks into the player's competitive in-season. This period included the final six games of their league season. The team won five of the six games losing only to the league winners. During the first week of the study, a lactate threshold/maximal oxygen uptake (VO_{2max}) test (LT/VO_{2max}) was completed replicating the protocol previously reported by Akubat et al. (2012). For the following six-week period, the participants' completed their regular academy and club training and matches. Training consisted of predominantly team-based tactical and skills training and physical conditioning, typically lasting 60 to 120 min. Players typically had a rest day following a match, before returning to training 48 h later. Participants' were regular first team players and completed the training as prescribed by their academy or club coaches. To monitor their internal and external loads during all training sessions and matches participants wore heart rate (HR) and MEMS devices. On arrival and prior to all training sessions players completed the Well-being Questionnaire (WB) (Rating perceptions of; fatigue, sleep quality, general muscle soreness, stress levels and mood) [7] to assess their subjective fatigue. Ethical approval for the study was obtained from the institutional ethics committee at Newman University (2015-10-21-1503753/1982).

2.2. Subjects

Ten academy rugby players (five forwards, and five backs) competing in the current champions of the Association of Colleges Regional Elite League agreed to participate in the study (mean (*SD*) age: 18.4 (1.0) years, height: 181.3 (5.9) cm, body mass: 85.9 (13.0) kg, VO_{2max}: 56 (6.7) $mL \cdot kg^{-1} \cdot min^{-1}$). The academy team is a college-based team aligned with a senior team competing in the National League One. The players' normal weekly training involved three to four pitch-based rugby sessions (120 min pre-session) plus an 80 min competitive match each Wednesday afternoon. Eight of the ten participants also trained and competed for their local rugby union club at under-18 or senior level.

2.3. Physiological Testing

Players avoided any strenuous exercise 48 h prior to the VO_{2max}/LT test. On arrival in the morning (non-fasted state) and prior to the test each participant was instructed on arrival to lie supine for ten minutes to assess their resting HR (Polar T34, Polar Electro Oy, Kempele, Finland). The lowest 5 s HR was recorded as their resting heart rate (HR_{rest}). To determine each participants heart rate-blood lactate relationships, maximal heartrate (HR_{max}), VO_{2max} and velocity at VO_{2max} (vVO_{2max}), each participant completed an incremental and ramp treadmill test (VO_{2max}/LT) (h/p cosmos mercury 4.0; h/p Cosmos, Nussdrof-Traunstein, Germany). The protocol consisted of six four minute stages at 6, 8, 10, 12, 14 and 16 $km \cdot h^{-1}$, with a one minute rest period between stages, during which a fingertip capillary blood sample was taken and immediately analysed for blood lactate using a portable analyser (Lactate Pro 2, Arkray KDK, Kyoto, Japan). One minute after completion of the six stages, participants completed a ramp protocol consisting of an increase in speed at a rate of 1 km·h^{-1}·min^{-1} starting at 16 km·h^{-1}. Participants were instructed to run until volitional exhaustion. HR data were recorded from a portable HR monitor (Polar T34, Polar Electro Oy). Achievement of VO_{2max} was considered once at least 2 of the following was attained; (1) a plateau in VO_2 despite increased speeds, (2) an RER above 1.10, (3) a HR ± 10 b·min^{-1} of age predicted HR_{max}. After the test, breath-by-breath values were visually inspected and VO_{2max} was defined as the highest 30 s mean value obtained during the test. The mean HR in the final minute of each stage was used for subsequent analyses. Expired air was analysed continuously during the test using a breath-by-breath system (MetaLyzer 3B, Cortex Biophysik, Leipzig, Germany). The velocity at 2 mmol·L^{-1} (vLT) and at 4 mmol·L^{-1} (vOBLA) were also obtained as measures of submaximal aerobic fitness [9,17,18].

2.4. Training Load

TL was calculated using different methods based on HR, sRPE and Microelectritromechanical systems (MEMS) (GPS 10 Hz, Tri-axial accelerometer 100 Hz; Catapult S5, firmware 6.75, Catapult Innovations, Melbourne, Australia). They were measured for each player in every training session and competitive match for six weeks during the regular season, from November to December. HR was measured using a short-range telemetry HR transmitter strap recording at 1 s intervals (Polar Team 2 System, Polar Electro Oy). Raw HR data for each training session and match were exported into dedicated software to determine individual session individualised Training Impulse (iTRIMP), Banister's TRIMP (bTRIMP), Lucia's TRIMP (luTRIMP) and Edward's TRIMP (eTRIMP) [19]. Calculation of bTRIMP were based on training duration, HR, and a weighting factor using the following formula where; $\Delta HR = (HR_{ex} - HR_{rest})/(HR_{max} - HR_{rest})$, e equals the base of the Napierian logarithms, 1.92 equals a generic constant for males and x equals ΔHR:

$$\text{bTRIMP} = \text{duration training (minutes)} \times \Delta HR \times 0.64e^{1.92x}$$

Edwards TRIMP [19] was calculated based on time spent in five HR zones and multiplied by a zone specific weighting factor: duration in zone 1 (50–59% of HR_{max}) multiplied by 1, duration in zone 2 (60–69% HR_{max}) multiplied by 2, duration in zone 3 (70–79% HR_{max}) multiplied by 3, duration in zone 4 (80–89% HR_{max}) multiplied by 4 and duration in zone 5 (90–100% HR_{max}) multiplied by 5. An adapted version of luTRIMP was calculated by multiplying time spent in three HR zones based around HR at LT and OBLA; where duration in zone 1 (≤HR at LT) is multiplied by weighing factor 1, duration in zone 2 (>HR at LT and <HR at OBLA) multiplied by 2 and duration in zone 3 (≥HR at OBLA) multiplied by weighting factor 3. The iTRIMP was calculated as per the method previously described by Manzi et al. [3,18] and Taylor et al. [9]. Approximately 30 min after each training session and match, players reported their RPE using the method of [20]. Each player was asked how hard they found each training session or match, reporting their subjective perception of effort using the Borg 10-point category-ratio scale. Players' sRPE was subsequently calculated as the RPE multiplied by the duration of the training session or match. Players were familiarised with the use of the RPE scale for a three-week period prior to the start of the six-week study period.

External training load was measured with a MEMS device. The reliability of MEMS devices has previously been demonstrated for the measurement of speed and distance in team sports [21,22]. MEMS devices were switched on at least ten minutes prior to each training session and match to ensure a full satellite signal. Players were fitted with the same HR and MEMS device for each session. The MEMS device was placed in a pouch positioned between the players' scapulae. After every training session, the recorded data were downloaded onto a laptop using the manufacturer's software (Sprint 5.1, Catapult Innovations). External load measures were determined from MEMS activity data. Activity was examined for total distance (TD) and distance covered at high-speed. Arbitrary predetermined high-speed distance thresholds were set at $\geq$15 km·h^{-1} (HSD) and $\geq$18 km·h^{-1} (VHSD) in accordance with previous studies [21,22]. Additionally, each player's vOBLA (vOBLA ranged from 8.7 to 13.1 km·h^{-1}) was employed to set an individualised high-speed distance threshold (iHSD).

2.5. Subjective Well-Being

Every morning prior to training, typically between 8:00 and 8:30 am, participants completed the well-being questionnaire [7] to assess their perceptions of fatigue, sleep quality, general muscle soreness, stress levels and mood using a five-point scale which used written descriptions for each of the five variables (Table 1). The well-being questionnaire is based on the recommendations of Hooper et al. [7] and its relationship to neuromuscular and endocrine measures following match-play in a similar rugby cohort. Each variable was scored on a 1 to 5 scale, where 1 described very poor levels of each variable and 5 described very good levels of each variable [7]. Players used a pen to complete a paper copy of the questionnaire on each occasion and did not discuss questionnaire responses with each other. Furthermore, any unusual responses where checked with each player by the researcher only to ensure players interpreted the question correctly. All data was observational and was not used to inform any of the training during the study period. All players were given instructions on the use of the questionnaire and familiarised with the questionnaire over the previous two months of the season.

Table 1. The well-being questionnaire that was completed during the study [7].

	1	2	3	4	5
FATIGUE	Always tired	More tired than normal	Normal	Fresh	Very fresh
SLEEP QUALITY	Insomnia	Restless sleep	Difficulty falling asleep	Good	Very restful
GENERAL MUSCLE SORENESS	Very sore	Increase in soreness/tightness	Normal	Feeling good	Feeling great
STRESS LEVELS	Highly stressed	Feeling stressed	Normal	Relaxed	Very relaxed
MOOD	Highly annoyed: irritable: down	Snappiness at team-mates, family, and co-workers	Less interested in objects & or activities than usual	A generally good mood	Very positive mood

2.6. Statistical Analysis

To avoid recent concerns about misinterpretation of p-values [23] Bayesian analysis was used. Bayesian analysis allows the use of domain specific knowledge, permits direct probability statements to be made around each parameter and estimates of uncertainty around the parameter values [24]. To maximize the amount of data collected for training and match loads the participants volunteered from the first 15 squad, we recruited the maximum number of participants available from the first 15 squad. Updating knowledge using Bayesian analysis is legitimate even with very few data points, for this study the average number of data points per player was 35.2 $\pm$ 10.9. Precision rather than power is the usual goal of Bayesian analysis; where priori sample size calculations are used instead of sample size calculations. To address this 95% CI's have been included in the table. The probabilities and percentages reported can be interpreted as the probability or percentage of a difference between the control condition (TL) and the questionnaire responses.

Due to the day-to-day data producing multiple observations for the same participant, traditional multiple regression techniques were not suitable as they assume each observation is independent [24]. Therefore, to assess the relationship between each external and internal training load measure and the next day's subjective well-being, a Bayesian random intercept model was used, where individual y intercepts could vary. These multiple regression models were applied using the *brms* package in R statistics program [25,26]. For each player the internal and external load measures for each training session, on each day of the study were set as the independent or predictor variable. The next-day subjective well-being score for each player was set as the dependent variable. Weakly informative priors were used in the models. The prior used for the intercept was Student t- distribution with 3 degrees of freedom (ν), the location parameter (μ) the median of the response variable, and the scale parameter (σ) the median absolute deviation of the response variable. Improper flat priors were used for all b coefficients in the model. The priors for standard deviation and sigma were restricted to be non-negative, using a half Student t- distribution prior with 3 degrees of freedom, a zero location and a scale parameter that is 2.5 or the median absolute deviation of the response variable of greater than 2.5. No groupings where included in the models, just intercepts for individual players could vary. The analysis produces coefficients for the fixed effects and random effects. Fixed effects are interpreted the same way as traditional regression coefficients; for every single unit of a given well-being score, a given TL increases by the value of the B_1 coefficient on average [26]. In addition, the probability that any change is likely to be greater or less than zero was calculated from posterior samples generated by the model (R package version 1.0.136, Vienna, Austria).

3. Results

During the six-week in-season study period internal and external load measures and subjective wellbeing questionnaires were obtained from a total of 164 training observations for the ten participants. Players competed in an average of 6 ($\pm$2.0) matches during the study period. To identify the feasibility of relationship between each TL measure and wellbeing variable and provide guidance for coaches to better manage players' well-being, the parameter estimate was multiplied for each load measure to elicit a change of 1 on the well-being questionnaire. The mean (MML) and highest match load (HML) in the study period is presented to give context to the required changes in load to manipulate questionnaire responses.

3.1. Internal Load Measures

Internal load measures sRPE (R^2 = 0.34), iTRIMP (R^2 = 0.32) and bTRIMP (R^2 = 0.31) demonstrated a 95% to 98% chance of a negative relationship with next-day total wellbeing scores, with the most likely relationship being classified as moderate (Table 2). All internal load measures explained between 66% and 67% of the variance in changes in next-day subjective stress (Table 2), with a 59% to 88% chance of a negative relationship. The weakness of this result is that the required change in all internal load measures to produce a change of one in next-day subjective stress was greater than the highest recorded match load (HML) reported during this study. The required change in these load measures to improve players' total well-being was between 15% and 18% of the HML. Whilst these internal load measures demonstrate the feasibility to manipulate daily training to improve total wellbeing although they only explain between 31% and 34% of the variance in those changes. All other relationships between internal load measures and wellbeing measures explained less than 39% of the variances in change (Table 2).

3.2. External Load Measures

All external load measures demonstrated the strongest relationships with next-day subjective stress (Table 3). External load measures TD, PL, iHSD and HSD demonstrated a 71% to 88% chance of a negative relationship, with the most likely relationship being classified as very strong (R^2 = 0.65). The required change in TD, PL, iHSD and HSD to improve players' next-day subjective stress by one was greater than the HML reported in this study. Similar to the internal load measures, external load measures explained between 33% and 37% of the variance in changes in next-day total wellbeing, with a 54% to 83% chance of a negative relationship. The required load to produce a change of one in next-day total wellbeing was between 13% and 19% of the HML produced in this study. All other external load measures explained similar or less of the variance in changes in next-day wellbeing measures (Table 3). Like the internal load measures, no load measure explained a suitably high percentage of the variance in changes combined with feasible changes in load to be able to manipulate next-day wellbeing.

Table 2. Bayesian linear mixed model analysis of the relationship between internal load measures (independent variable) and next-day well-being questionnaire (WB) (*n* = 10).

Load Measure		Well-Being Questionnaire (WB)					
		Fatigue	**Sleep Quality**	**Muscle Soreness**	**Stress Levels**	**Mood**	**Total Well-Being**
sRPE (AU)	R^2	**0.16**	**0.12**	**0.13**	**0.67**	**0.39**	**0.34**
HML = 909.20 MML = 504.72 (±96.51)	Estimate (95% CI)	−0.00 (−0.003 to 0.000)	−0.00 (−0.002 to 0.001)	−0.00 (−0.003 to −0.001)	−0.00 (−0.002 to 0.001)	0.00 (−0.001 to 0.002)	−0.00 (−0.008 to −0.000)
	Probability Δ < 0 <	0.97 < 0 < 0.03	0.76 < 0 < 0.24	1.00 < 0 < 0.00	0.88 < 0 < 0.12	0.33 < 0 < 0.67	0.98 < 0 < 0.02
iTRIMP (AU)	R^2	**0.12**	**0.12**	**0.15**	**0.66**	**0.39**	**0.32**
HML = 726.42 MML = 298.43 (±71.11)	Estimate (95% CI)	−0.00 (−0.005 to 0.002)	−0.00 (−0.003to 0.001)	−0.01 (−0.007 to 0.001)	−0.00 (−0.003 to 0.002)	−0.00 (−0.003 to 0.002)	−0.01 (−0.018 to 0.000)
	Probability Δ < 0 <	0.84 < 0 < 0.16	0.53 < 0 < 0.47	1.00 < 0 < 0.00	0.76 < 0 < 0.24	0.63 < 0 < 0.37	0.98 < 0 < 0.02
luTRIMP (AU)	R^2	**0.11**	**0.11**	**0.08**	**0.66**	**0.39**	**0.30**
HML = 295.60 MML = 156.34 (±32.53)	Estimate (95% CI)	−0.00 (−0.010 to 0.004)	−0.00 (−0.010 to 0.002)	−0.01 (−0.012 to 0.000)	−0.00 (−0.006 to 0.003)	−0.00 (−0.006 to 0.004)	−0.01 (−0.027 to 0.007)
	Probability Δ < 0 <	0.80 < 0 < 0.12	0.33 < 0 < 0.67	0.97 < 0 < 0.03	0.71 < 0 < 0.29	0.68 < 0 < 0.32	0.88 < 0 < 0.12
eTRIMP (AU)	R^2	**0.12**	**0.11**	**0.10**	**0.66**	**0.39**	**0.30**
HML = 350.77 MML = 221.14 (±48.42)	Estimate (95% CI)	−0.00 (−0.007 to 0.002)	−0.00 (−0.004 to 0.004)	−0.01 (−0.009 to 0.001)	−0.00 (−0.004 to 0.003)	−0.00 (−0.004 to 0.003)	−0.01 (−0.024 to 0.000)
	Probability Δ < 0 <	0.86 < 0 < 0.14	0.55 < 0 < 0.45	0.99 < 0 < 0.01	0.59 < 0 < 0.41	0.62 < 0 < 0.38	0.96 < 0 < 0.04
bTRIMP (AU)	R^2	**0.11**	**0.11**	**0.10**	**0.66**	**0.39**	**0.31**
HML = 353.56 MML = 168.79 (±38.38)	Estimate (95% CI)	−0.00 (−0.001 to 0.004)	−0.01 (−0.007 to 0.005)	−0.01 (−0.013 to 0.001)	−0.00 (−0.007 to 0.004)	−0.00 (−0.006 to 0.005)	−0.02 (−0.035 to 0.002)
	Probability Δ < 0 <	0.76 < 0 < 0.24	0.64 < 0 < 0.36	0.99 < 0 < 0.01	0.68 < 0 < 0.32	0.59 < 0 < 0.41	0.95 < 0 < 0.05

Table 3. Bayesian linear mixed model analysis of the relationship between external load measures (independent variable) and next-day well-being questionnaire (WB) (*n* = 10).

		Well-Being Questionnaire (WB)					
		Fatigue	**Sleep Quality**	**Muscle Soreness**	**Stress Levels**	**Mood**	**Total Well-Being**
TD (m)	R^2	**0.22**	**0.09**	**0.05**	**0.65**	**0.34**	**0.33**
HML = 9422.00 MML = 5570.96 (±1003.03)	Estimate (95% CI)	−0.00 (−0.000 to 0.000)	−0.00 (−0.001 to 0.000)	−0.00 (−0.000 to 0.000)	−0.00 (−0.000 to 0.000)	−0.00 (−0.000 to 0.000)	−0.00 (−0.002 to 0.000)
	Probability Δ < 0 <	0.67 < 0 < 0.33	0.81 < 0 < 0.19	0.55 < 0 < 0.45	0.81 < 0 < 0.19	0.65 < 0 < 0.35	0.86 < 0 < 0.14
PL (AU)	R^2	**0.22**	**0.10**	**0.05**	**0.65**	**0.34**	**0.34**
HML = 930.00 MML = 531.64 (±99.43)	Estimate (95% CI)	−0.00 (−0.005 to 0.002)	−0.00 (−0.005 to 0.003)	−0.00 (−0.003 to 0.004)	−0.00 (−0.004 to 0.002)	−0.00 (−0.005 to 0.001)	−0.01 (−0.017 to 0.004)
	Probability Δ < 0 <	0.74 < 0 < 0.26	0.92 < 0 < 0.08	0.46 < 0 < 0.54	0.75 < 0 < 0.25	0.83 < 0 < 0.17	0.88 < 0 < 0.12
iHSD (m)	R^2	**0.23**	**0.09**	**0.05**	**0.65**	**0.36**	**0.37**
HML = 3052.00 MML = 1673.80 (±367.01)	Estimate (95% CI)	−0.00 (−0.001 to 0.000)	−0.00 (−0.001 to −0.000)	−0.00 (−0.001 to 0.000)	−0.000 (−0.001 to 0.000)	−0.00 (−0.001 to 0.001)	−0.00 (−0.005 to 0.000)
	Probability Δ < 0 <	0.84 < 0 < 0.16	0.86 < 0 < 0.14	0.78 < 0 < 0.22	0.85 < 0 < 0.15	0.78 < 0 < 0.22	0.97 < 0 < 0.03
HSD (m)	R^2	**0.24**	**0.10**	**0.06**	**0.65**	**0.35**	**0.37**
HML = 2415.00 MML = 1249.04 (±303.14)	Estimate (95% CI)	−0.00 (−0.002 to 0.000)	−0.00 (−0.000 to −0.000)	−0.00 (−0.001 to 0.000)	−0.00 (−0.001 to 0.000)	−0.00 (−0.001 to 0.001)	−0.00 (−0.001 to 0.000)
	Probability Δ < 0 <	0.89 < 0 < 0.11	0.84 < 0 < 0.16	0.85 < 0 < 0.15	0.88 < 0 < 0.12	0.75 < 0 < 0.25	0.97 < 0 < 0.03
VHSD (m)	R^2	**0.24**	**0.09**	**0.05**	**0.64**	**0.34**	**0.33**
HML = 787.00 MML = 389.41 (±105.34)	Estimate (95% CI)	−0.00 (−0.004 to 0.001)	−0.00 (−0.003 to 0.001)	−0.00 (−0.003 to 0.001)	−0.00 (−0.003 to 0.001)	−0.00 (−0.002 to 0.002)	−0.00 (−0.011 to 0.002)
	Probability Δ < 0 <	0.86 < 0 < 0.14	0.86 < 0 < 0.14	0.76 < 0 < 0.24	0.75 < 0 < 0.25	0.54 < 0 < 0.46	0.90 < 0 < 0.10

4. Discussion

The findings of this study are the first to examine the relationship between internal and external load measures with next-day subjective well-being in rugby union players during a competitive in-season period. External and internal load measures explained between 28% and 36% of the variance in next-day total WB with a 77% to 98% chance of a negative relationship. Therefore, these results question the suitability and validity of commonly used internal/external TL and well-being response measures to inform the training process. That is, an increase in TL would reduce (improve) a player's perception of total WB. Furthermore, the required load to produce a change of 1 in the total WB was between 15% and 24% for internal loads and between 15% and 29% of the mean match loads for the study period. Practically this requires weekly total distance to be reduced by 1809 m (32% of weekly mean TD) and HSD by 336 m (14% of weekly mean HSD). Whilst these values appear practical for individual conditioning training, removing players from team-based training is more challenging given the position specific demands involved in the tactical demands of rugby union. A range of internal load measures explained between 66% and 67% of the variance in changes in next-day subjective stress, with a 59% to 88% chance of a negative relationship. External load measures provided the most practical measures as they required a decrease in load of between 7% and 23% of the maximal match load to reduce perceived stress. The required change in load all internal load measures to change a player's wellbeing by one was greater than the maximal weekly loads reported in this study. Consequently, a player would have to miss an entire weeks training to improve their well-being score. Therefore, whilst internal loads demonstrate a strong relationship with next-day well-being, the results question the practical suitability and meaningfulness of this relationship. All other internal and external TL metrics explained similar or less of the changes in the next-day WB subscales. From a practical perspective, current technology allows coaches to monitor external loads in real time during training. Therefore, manipulating external load measures such as TD, PL and HSD during the training week provide the most practical measures to manage player's perceived stress levels as measured by the WB questionnaire.

In academy rugby union players' wellbeing (motivation, recovery, sleep quality and muscle soreness) are sensitive to next-day changes following a high training load protocol [27]. Furthermore, wellbeing (fatigue, muscle strain, hamstring strain, pain/stiffness, power, sleep quality, stress) improved daily during the training week following high match loads in Australian Football players [28]. These findings contrast with previous findings in elite youth soccer players during the competitive in-season [29]. Relationships have been reported between sRPE and pre-training subjective well-being (WB) in collegiate American football players [28], professional soccer players [29] and Australian football players [30,31]. These previous studies identified have explained between 7% and 37% of the variance between sRPE and changes in perceptions of sleep, fatigue, stress and muscle soreness. Importantly, these studies compared subjective well-being immediately before training. It has previously been suggested that these pre-exercise well-being questionnaires are valid and reliable tools to identify changes in perceived fatigue in team sports [28]. Recently Duignan et al. [14] has suggested that the relationship between self-report measures and training loads remains unclear and further assessment is required to establish their suitability to detect fatigue. Therefore, it is entirely possible that the relationships are not only confounded by the TL variables but also the suitability of the outcome measures.

A limitation of this study was the small sample size. The study population was a convenience sample limited to the fifteen players who were regular first team players, as such would consistently play in all matches during the study period. To address the small sample size, a strength of using Bayesian analysis in this study is that the analysis is based around data points compared to sample size found in typical frequentist methods. Precision rather than power is the usual goal of Bayesian analysis and its priori sample size calculations. Follow up studies with more participants and using Bayesian analysis would help confirm the findings of this study. Both physiological and psychological factors have been shown to influence the accuracy of wellbeing questionnaires [7,8]. Additional stresses such as academic and social can have greater impact on perceptions of fatigue in academy age groups than elite senior players [27]. Additionally, the length of the rating scales used in typical well-being questionnaires may not allow athletes to fully describe their subjective fatigue. The small variance explained by the changes in WB makes their use to inform the dose-response relationship between TL and perceived fatigue is questionable. In a previous study [30] it was highlighted that individual responses to bouts of high TL, where players with the highest VO_{2max} typically reporting lower RPE for each exercise bout. In contrast, two players with similar VO_{2max} values reported different perceptions of fatigue. As such, subjective psychological responses are more complex and influenced by more than the physiological responses to training and match-play alone [12,30,31]. Ultimately, well-being questionnaires may require more sensitive scales to quantify the complex multifactorial nature of subjective fatigue more fully, of which the TL completed is only one factor.

The data from this investigation would suggest no more than 33% to 36% of changes in total WB can be explained by external load measures (TD, PL, iHSD and HSD). This investigation viewed in the wider scope of the purpose of athlete monitoring would suggest caution is required if sports scientist is planning to use manipulation of TL to influence outcomes for subjective fatigue in rugby players. It could be that the unique nature of rugby and other team sports that involve contact and collisions during training and match-play provides an additional component that influences players perception of well-being that is not present in other teams' sports such as soccer. As such, further research is required into the relationship between TL measures and subjective fatigue measures to better understand to what extent a feasible relationship between measures of TL and subjective measures is possible and able to influence the training process. There is the possibility that typically collected training load measures do not explain larger proportions of perceptions in fatigue. Consequently, the hope of a dose-response relationship where we can confidently manipulate TL to impact levels of fatigue may not be possible at present. In this instance reacting to the response may be the only possible course of action [2].

5. Conclusions

The real training environment with trained academy rugby union players from which this data was collected allows for important practical findings to be made. Given that at present coaches can monitor external load metrics live during training, external loads provide the most practical options for the manipulation of TL. The findings of this study suggest external load measures TD, PL, iHSD and HSD explain 33% to 36% of the changes in next-day total WB. That is, a decrease of 821 m (TD), 247 m (iHSD) or 183 m (HSD) has an 88% to 96% chance of improving player's perception of total WB. Practically, if a player reports a reduction in their wellbeing and specifically their perception of stress in the morning prior to training, coaches should look to reduce the high-intensity component of that days training. This is especially important in the days leading into match-day and should form part of the tapering process. This should reduce the impact of poor well-being negatively impacting match performance. Whilst it might be possible for coaches to reduce the volume of TD and high-intensity training during training week leading into a match to improve total WB and perceived stress, the 30% to 60% of variance explained warrants further caution when coaches interpret these responses in isolation.

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